SPATIAL VARIABILITY AND CORRELATION OF SELECTED SOIL PROPERTIES IN THE AP HORIZON OF A CRP GRASSLAND

J. D. Jabro, W. B. Stevens, R. G. Evans, W. M. Iversen

ABSTRACT. *Knowledge of the spatial variability of soil properties in agricultural fields is important for implementing various precision agricultural management practices. This article examines spatial variation of selected soil physical and chemical properties and explores their spatial correlation in the Ap horizon of a Lihen sandy loam soil (sandy, mixed, frigid Entic Haplustoll) within a field of grass-alfalfa Conservation Reserve Program (CRP) land. Soil measurements were made on a 16 × 36-m grid sampling pattern. Soil properties including penetration resistance (PR), bulk density (ρ_b), and gravimetric water content (θ_m) were measured by collecting undisturbed soil cores from 5- to 10-cm and 20- to 25-cm depths. Additional disturbed soil samples were collected for particle size distribution, electrical conductivity (EC_e), and pH analysis. The two depths were averaged for the assessment of spatial distribution, relationships and interpolation of soil properties. Soil saturated hydraulic conductivity (K_s) and total porosity (ε_T) for the 0- to 25-cm depth were estimated from ρ_b, θ_m, and volumetric water content at field capacity (FC) level. Soil properties were analyzed using both classical and geostatistical methods that included descriptive statistics, semivariograms, cross-semivariograms, spatial kriged and co-kriged prediction maps and interpolation. Results indicated that small to moderate spatial variability existed across the field for soil properties studied. Furthermore, cross-semivariograms exhibited a strong negative spatial interdependence between soil PR and θ_m, ε_T, and lnK_s. Spatial variability of soil θ_m, ρ_b, PR, ECe, pH, and clay content and their spatial correlation in the Ap horizon of the CRP grassland were attributed to a combination of previous farming practices, topographic characteristics, vegetation history, soil erosion, and weather conditions at this site.*

Keywords. *Spatial variability, Statistics, Semivariogram, Cross-semivariogram, Kriging.*

Soil properties vary over space and time. Spatial variability is a term indicating changes in the value of a given property over space (Ettema and Wardle, 2002). It can be assessed using classical descriptive statistics (i.e., mean, range, coefficient of variation) or geostatistics (i.e., semivariogram, autocorrelation, cross-semivariogram, kriged, and co-kriged maps).

Knowledge of the spatial variability of soil properties is essential for site-specific soil management and evaluation of various agricultural land management practices. Spatial variability and distribution of soil properties within agricultural fields can be classified as static (e.g. texture, mineralogy) due to soil formation processes or dynamic (e.g. water content, compaction, electrical conductivity, carbon content) caused by various land management practices (Jabro et al., 2006). Both static and dynamic soil physical and chemical properties vary across agricultural fields, contributing to variable crop yields. Thus characterization of the spatial variability of these soil properties within agricultural fields is essential for site-specific management, also referred to as precision agriculture practices, and can help explain significant effects on the spatial distribution of crop yield and quality.

Spatial variability and correlation of various soil properties across the landscape has been intensively studied and evaluated during the past two decades using both classical statistics and the theory of regionalized variables as evaluated using geostatistical methods (Cambardella et al., 1994; Fulton et al., 1996; Gaston, et al., 2001; Huang et al., 2001; Iqbal et al., 2005; Mzuku et al., 2005; Guo-Shun et al., 2008). These researchers have shown that various soil properties can vary significantly within a single field.

Geostatistics have proved useful for assessing spatial variability of soil properties and have increasingly been utilized by soil scientists and agricultural engineers in recent years (Webster and Oliver, 2001; Iqbal et al., 2005). Furthermore, geostatistical methods have been adopted and used in site-specific management applications, soil sampling strategies and assessment of farm management styles and decisions.

Semivariograms and cross-semivariograms have been used to characterize and model spatial variance of data to assess how data points are related with separation distances while kriging uses modeled variance to estimate values between samples (Journel and Huijbregts, 1978). Kriging and co-kriging are common geostatisical procedures that have been used for optimal estimation and spatial interpolation of values at unsampled locations. Co-kriging uses more than one variable in spatial interpolation process. It employs a

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second variable to estimate values of primary variable of interest that were assumed to be spatially dependent (Matheron, 1963; McBratney and Webster, 1983; Davis, 1986).

Little information has been reported on the spatial variability of soil properties in long-term Conservation Reserve Program (CRP) grassland fields. The 4.75-ha sub-site used in this study presented a rare opportunity to study effects of past agricultural management systems on spatial relationships among selected soil properties. Therefore, the objectives of this study were to i) characterize field-scale spatial variability of selected soil properties in the Ap horizon of dryland grass-alfalfa field in the semiarid region of the Northern Great Plains that had been under CRP management for more than 20 years; and, ii) to explore the spatial interdependence between penetration resistance (PR) and other soil properties using cross-semivariance analysis.

We selected the Ap horizon for soil sampling and measurements because this layer represented the plough layer (0- to 25-cm depth) and soil properties at this layer are most affected by land management practices.

Materials and Methods

Soil Description, Data Collection, and Site Characterization

A study was conducted in April 2005 on a CRP grassland site located at MonDak Irrigation Research Farm in the Nesson Valley area located approximately 37 km east of Williston, North Dakota (48.1640°N, 103.0986°W). The topography of land (fig. 1) gradually slopes from NW to SE at approximately 2%. The soil is mapped as Lihen sandy loam (sandy, mixed, frigid Entic Haplustoll) consisting of very deep, somewhat excessively or well drained, slightly sloping soil that formed in sandy alluvium, glacio-fluvial, and eolian deposits in places over till or sedimentary bedrock (www.ftw.nrcs.usda.gov).

Particle size distribution analysis indicated that the textural class of the Ap horizon (0-25 cm) fell consistently within the sandy loam classification. The amount of sand, silt, and clay at 0- to 25-cm depth ranged from 53.4 to 77.4%, 6.7 to 25.8%, and 12.8 to 23.2%, respectively. Soil bulk density at 0- to 25-cm depth ranged from 1.31 to 1.65 Mg m^{-3}. Climate at the location is semi-arid with an average annual rainfall of about 360 mm, of which about 40% typically occurs in the months of May, June, and July.

The experiment was conducted on a 4.5-ha portion of a 65-ha dryland farm that was converted in the spring of 2005 to an irrigated research farm. After being broken out of native prairie in about 1905, the site was managed as a dryland small grains farm for approximately 80 years using conventional tillage (i.e., moldboard plough) and alternating years of crop production and fallow. Wind erosion of soil particles was severe at times during this period. Because of its erodibility, the land was seeded in 1988 to a mix of crested wheatgrass [*Agropyron cristatum* (L.) Gaertn.] and alfalfa (*Medicago sativa* L.) then placed in the USDA CRP for 10 years (Wayne Vance, personal communication, 2006). From 1998 to 2004, the site was managed as a dryland perennial hay field and was cut for hay when precipitation was sufficient to produce a harvestable crop.

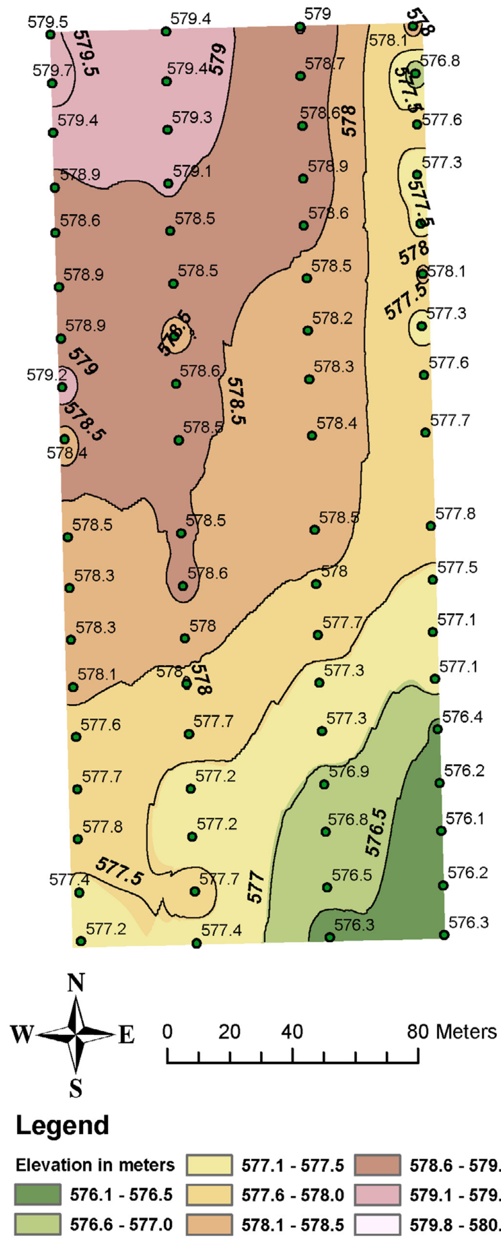

Figure 1. Map showing elevation contours and grid sampling points.

A geo-referenced sampling scheme using Differential Global Positioning System (Omnistar, Inc., Houston, Tex.) was utilized for acquiring soil samples and making soil compaction measurements. Soil properties measured at the site included penetration resistance (PR) as an indicator of soil strength or compaction. Soil bulk density, Mg m^{-3} (ρ_b) and gravimetric water content, g g^{-1} (θ_m) were measured by collecting undisturbed soil cores from 5- to 10-cm and 20- to 25-cm depths using a standard 5-cm inner diameter probe. Additional disturbed soil samples were collected for electrical conductivity, mS m^{-1} (ECe) and pH analyses. Saturated soil extracts were prepared (Rhoades, 1996) and used to measure ECe and pH with an electrical conductivity meter (Model #3084, Amber Science, Inc., Eugene, Oreg.) and pH meter, respectively.

Soil PR was measured using a digital penetrometer (Field Scout, SC 900 Soil Compaction Meter, Spectrum Technologies, Inc., Plainfield, Ill.) at three different locations within an approximately 30-cm radius of where soil cores for bulk density were extracted. Soil PR readings were recorded in 2.5-cm increments to a depth of 25 cm and averaged from 0- to 25-cm soil depth for each plot.

Soil properties measurements were made on a 16- × 36-m grid sampling pattern forming 72 individual grid cells. Soil properties were measured at the center of each grid cell at depths of 0 to 10 cm and 20 to 25 cm, which represented the Ap horizon in this semi-arid environment. The two depths were averaged for the assessment of spatial distribution and relationship of soil properties.

Soil saturated hydraulic conductivity for the 0- to 25-cm depth was estimated from effective porosity (ϕ_e) and water contents at field capacity (FC) data (Suleiman and Ritchie, 2001) as:

$$K_s = 75 \times \left(\frac{\phi_e}{FC}\right)^2 \tag{1}$$

where K_s is the saturated hydraulic conductivity of the soil (cm d^{-1}) and ϕ_e is the effective soil porosity (total porosity (ε_T) minus water content at FC). The measured FC for Lihen sandy loam soil at 0- to 25-cm depth was 0.234 m^3 m^{-3} (Jabro et al., 2009). The total soil porosity (ε_T) was calculated from:

$$\varepsilon_T = 1 - \frac{\rho_b}{2.65} \tag{2}$$

where ρ_b was soil bulk density and 2.65 Mg m^{-3} was the soil particle density.

Statistical methods

Descriptive statistics, including mean, maximum, minimum and coefficient of variation (CV) were obtained for each soil property using SAS software (SAS Institute, 2003). Linear correlation coefficient analysis was performed among all soil physical properties. All data were checked for normality using SAS probit and frequency procedure, which indicated no need to transform the data prior to using geostatistical analysis except for ECe and K_s data. The probit procedure revealed that ECe and K_s data were best fit by a log-normal distribution and thus were log-transformed to attain normality.

A student t-test showed that there were no significant differences between the two depths for all measured soil variables except for PR thus allowing the two depths to be averaged for the assessment of spatial variability of soil properties using geostatistical methods.

Geostatistical analyses, including semivariogram, cross-semivariogram model fitting and kriging procedures, were carried out using GS+ (Gamma Design Software, 2004, Geostatistics for the Environmental Sciences, St. Plainwell, Mich.) to assess the degree of spatial variability of each soil property used in this study. Measurements of θ_m, ε_T, PR, $\ln K_s$, lnECe were block-ordinary kriged to produce interpolated spatial maps. Prior to applying geostatistical procedures, each soil variable used in this study was checked for presence of trends in the data, and for anisotropy at various directions (0, 45, 90 and 135 degrees). There were no trends in the data for all soil properties except for θ_m data where a linear trend was detected in northern direction.

Linear trends were removed by fitting a linear regression equation to the 18 means in northern direction calculated from four transects of moisture content data in eastern direction (Rajkai and Ryden, 1992). Isotropic semivariogram models were best fit to the experimental data. Residual sums of squares (RSS) in conjunction with R^2 were used to select the exact form and best fit of the semivariogram model. The RSS provides a sensitive, robust measure of how well the model fits the experimental semivariogram data, the lower the RSS, the better the model fits the data. A trial and error procedure based on optimization of both RSS and R^2 was used to select the best fit model to the experimental semivariance values for each soil property.

Semivariance is expressed in equation 3 as described by Journel and Huijbregts (1978) and Clark (1979).

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{z(x_i + h) - z(x_i)\}^2 \tag{3}$$

where $\hat{\gamma}(h)$ is semivariance for the interval distance class, h is the lag distance, $z(x_i)$ is the measured sample value at point x_i, $z(x_i+h)$ is the measured value at point x_i+h, and N(h) is the total number of pairs for lag interval h.

The spherical model defined in equations 4 and 5 provided the best fit for the experimental semivariance of soil PR, lnECe, and pH.

$$\gamma(h) = C_0 + C\left(\frac{3h}{2A} - \frac{1}{2}\left(\frac{h}{A}\right)^3\right) \text{ for } h \leq A \tag{4}$$

and

$$\gamma(h) = C_0 + C \text{ for } h > A \tag{5}$$

where C_0 is nugget effect value, C is the partial sill, (C_0+ C) is the sill or total semivariance, A is the range, and h is the distance. Note that $\gamma(h) = 0$ when $h = 0$. The three parameters of semivariograms models are defined according to Bai et al. (2009) as follows: "A nugget is the value of the semivariogram for a distance equal to zero. A non-null nugget may indicate either a systematic measurement error or that a spatial variation occurs at a scale smaller than that used for measurements. The sill is the final stable value of the semivariogram. The range is the distance at which the semivariance reaches that stable value."

The exponential model (eq. 6) is similar to the spherical model (eq. 5), in that it approaches the sill gradually and reaches the specified sill, (C_0+ C), at the specified range, A. However, the exponential model (eq. 6) approaches the sill asymptotically, with A representing the practical range, the distance at which the semivariance reaches 95% of the sill value (Journel and Huijbregts, 1978; Clark, 1979; Bohling, 2005).

The exponential model (eq. 6) provided the best fit for the experimental semivariance for ε_T and $\ln K_s$.

$$\gamma(h) = C_0 + C\left(1 - \exp\left(-\frac{h}{A}\right)\right) \text{ for h} \geq 0 \tag{6}$$

The Gaussian model is similar to the exponential model but assumes a gradual rise for the y-intercept (Journel and Huijbregts, 1978).

$$\gamma(h) = C_0 + C\left(1 - \exp\left(-\frac{h^2}{A^2}\right)\right) \text{ for h} \geq 0 \tag{7}$$

The Gaussian model defined in equation 7 provided the best fit for the experimental semivariance for original and de-trended data of soil θ_m.

Cross-semivariances were also calculated to examine a spatial relationship between two variables at the same location and then variables are said to be co-regionalized or interrelated (Heisel et al., 1999). The cross-dependence between two variables u and v has a cross-semivariogram expressed as:

$$\hat{\gamma}_{uv}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \Big[\{z_u(x_i + h) - z_u(x_i)\} \times \{z_v(x_i + h) - z_v(x_i)\}\Big] \quad (8)$$

where $\hat{\gamma}_{uv}(h)$ is cross-semivariance between u and v variables for the interval distance class, h is the lag distance, N(h) is the total number of pairs for lag interval h, $z_u(x_i)$ and $z_u(x_i+h)$ are the measured values of variable z_u, $z_v(x_i)$ and $z_v(x_i+h)$ are the measured values of variable z_v at points x_i and x_i+h, respectively (Journel and Huijbregts, 1978). The cross-semivariogram is positive when the values of u and v variables vary jointly or dependently, negative when the values of these two variables vary in opposite directions and null when the two variables vary independently (McBratney and Webster, 1983). The two variables are called co-regionalized and spatially dependent and are used in the co-kriging estimation technique (McBratney and Webster, 1983).

Maps of kriged and co-kriged predictions from fitted semivariograms and cross-semivariograms were produced for soil variables using ordinary block kriging interpolation with a block size of 2 × 2 m using GS+ software (Journel and Huijbregts, 1978). The accuracy of kriged and co-kriged maps was evaluated using cross validation statistical methods by comparing the actual and predicted values (Santra et al., 2008).

Results and Discussion

Descriptive Statistics

Descriptive statistics for soil properties selected in this study are given in table 1. The CV values of measured and estimated soil properties ranged between 3.4% for pH and 23.1% for K_s. The variability of soil properties within the study site was classified as low (0-15%) to medium (15%-75%) based on the CV values according to the groupings described by Dahiya et al. (1984). This indicates that PR and K_s exhibit medium variability while the remaining soil properties quantified in this study exhibit low variability (CV= 0 -15%) within the study area.

Table 1. Summary statistics for selected soil properties of 0- to 25-cm top soil.

Soil Property	Mean	Minimum	Maximum	CV%[a]
Moisture content, θ_m (g g^{-1})	0.099	0.079	0.132	11.6
Total porosity, ε_T (m^3 m^{-3})	0.419	0.377	0.468	4.7
Penetration resistance, PR (MPa)	1.93	1.27	2.70	16.7
Hydraulic conductivity, (K_s) (cm d^{-1})[b]	52.62	30.77	107.32	23.1
Electrical conductivity, ECe (mS m^{-1})[b]	56.85	36.30	68.50	44.5
pH	6.82	6.16	7.22	29.7

[a] CV is the coefficient of variation.
[b] Calculations are based on log-transformed data.

Linear correlation coefficients (r) between soil PR and θ_m, ε_T, and $\ln K_s$ were negative, moderate, and significant at the probability level less than 0.01. The r values between soil PR and θ_m, ε_T, and $\ln K_s$ were -0.45, -0.44, and -0.46, respectively.

The basis of the negative relationships between soil PR and θ_m, ε_T, and K_s is direct; that is, higher soil PR values are associated with smaller ε_T and lower θ_m levels in the soil. Water flow through the soil expressed by K_s is associated directly with soil ε_T and thus it is inversely affected by soil compaction.

Geostatistical Methods

Semivariogram Analysis

The isotropic semivariograms for θ_m (original and detrented data), ε_T, PR, $\ln K_s$, lnECe, and pH at 0- to 25-cm soil depth were computed and shown in figures 2A-2G, respectively. Semivariogram coefficients for each soil property with the best-fitted model are listed in table 2. The R^2 values in table 2 show that models fit the experimental semivariogram data very well for all soil properties except pH. Concurrently, the RSS values were extremely small for semivariogram models of all soil properties investigated in this study.

The nugget to sill ratio (C_0/C_0+C) expressed as the nugget ratio (Ersahin and Brohi, 2006; Mallants et al., 1996) was

Table 2. Coefficients of the theoretical semivariogram models of soil properties.

Soil Property	Model	Nugget, C_0	Sill, $C_0 + C$	Nugget Ratio, $\frac{C_0}{C_0 + C}$	Range, A (m)	RSS[a]	R^2
Moisture content (original data), θ_m (g g^{-1})	Gaussian	0.00005	0.00063	0.08	377	4.8×10^{-10}	0.96
Moisture content (detrended data), θ_m (g g^{-1})	Gaussian	0	0.000276	0	19	1.5×10^{-8}	0.57
Total porosity, ε_T (m^3 m^{-3})	Exponential	0.00024	0.0005	0.48	37	6.6×10^{-9}	0.80
Penetration resistance, PR (MPa)	Spherical	0.0218	0.1226	0.18	163	2.2×10^{-4}	0.98
Hydraulic conductivity, ln(K_s) (cm d^{-1})[b]	Exponential	0.0247	0.05	0.49	35	2.7×10^{-5}	0.88
Electrical conductivity, lnECe (mS m^{-1})[b]	Spherical	0.00623	0.017	0.36	76	9.3×10^{-5}	0.84
pH	Spherical	0.0025	0.054	0.05	23	1.6×10^{-4}	0.24

[a] RSS is the residual sums of squares for the theoretical semivariogram models.
[b] Analyses are based on log-transformed data.

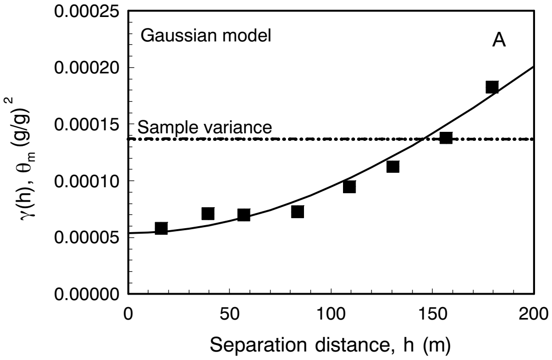

Figure 2A. Semivariogram of moisture content (original data), θ_m.

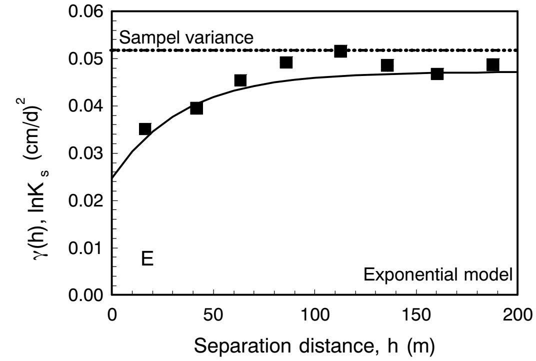

Figure 2E. Semivariogram of hydraulic conductivity, $\ln K_s$.

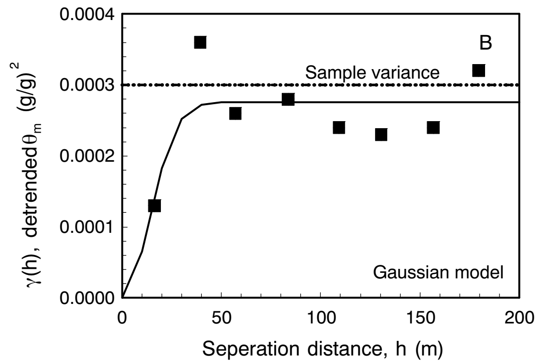

Figure 2B. Semivariogram of moisture content (detrended data), θ_m.

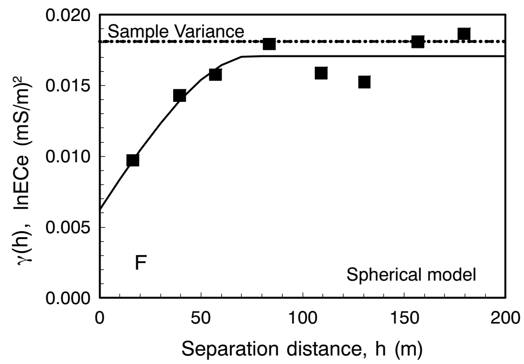

Figure 2F. Semivariogram of electrical conductivity, lnECe.

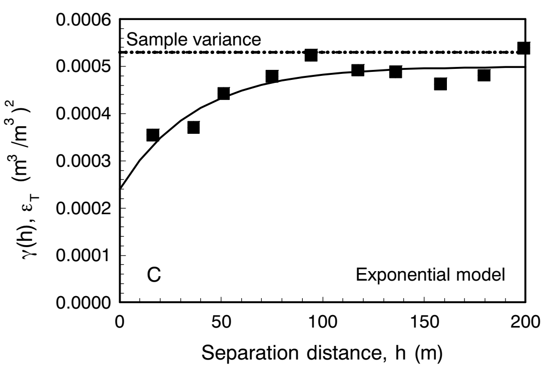

Figure 2C. Semivariogram of total porosity, ε_T.

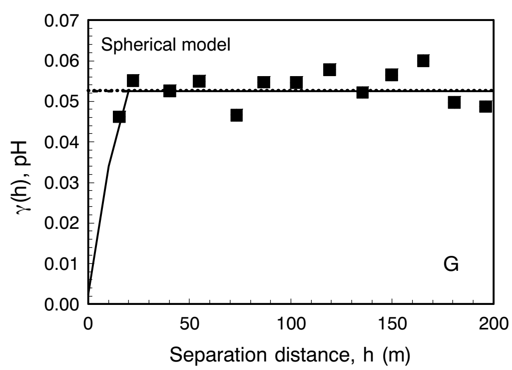

Figure 2G. Semivariogram of pH.

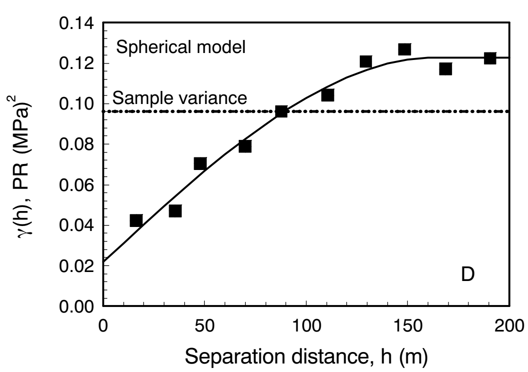

Figure 2D. Semivariogram of penetration resistance, PR.

calculated for each soil physical property and used to evaluate the degree of spatial dependence and correlation associated with each soil property (table 2). The nugget ratio values were then categorized into one of three classes to define distinctive spatial dependence in soil properties (Cambardella et al., 1994). A structural variance value close to zero indicates continuity in the spatial dependence.

If the nugget ratio was <0.25, the property was considered strongly spatially dependent; if the nugget ratio was >0.25 and <0.75, the property was considered moderately spatially dependent; and if the nugget ratio was >0.75, the property was considered weakly spatially dependent (Cambardella et al., 1994; Iqbal et al., 2005; Jabro et al., 2006).

The nugget ratio values from resulting theoretical semivariograms (figs. 2A-2G) indicate strong spatial dependencies for θ_m (both original and detrended data), PR, and Ph, and moderate spatial dependencies for ε_T, lnK_s, and lnECe parameters (table 2). However, the semivariograms for θ_m (detrended data), ε_T, lnECe, and pH show a nugget value close to zero or zero (table 2, figs. 2B, 2C, 2F, and 2G). A zero nugget effect value for soil properties indicates a smooth spatial continuity and dependency among adjacent sampling points (Journel and Huijbregts, 1978; Davis, 1986; Vieira and Gonzalez, 2003).

The ranges of spatial dependencies were large and vary between 23 m for pH to 377 m for θ_m indicating that the optimum sampling interval varies greatly among different soil properties. In general, results from both classical and spatial statistics indicated that small to moderate spatial variability existed across the field for all soil properties selected in this study.

Cross-Semivariogram Analysis

The isotropic cross-semivariograms of soil PR with θ_m, ε_T, and lnK_s are shown in figures 3A, 3B, and 3C, respectively. Cross-semivariograms were calculated to explore and determine spatial interrelations using co-regionalized models between PR and other measured soil properties. Among different theoretical cross-semivariogram models tested, Gaussian, spherical, and exponential models were best fitted to the experimental values of PR with θ_m, ε_T, and lnK_s, respectively. Cross-semivariogram models and their spatial interrelations coefficients are presented in table 3.

The R^2 and the RSS for theoretical cross-semivariogram models to fit the experimental values between soil PR and θ_m, ε_T, and lnK_s are given in table 3. The R^2 and RSS values in table 3 show that models fit the experimental cross-semivariance data exceptionally well in all cases used in this study.

Once again, using the criteria suggested by Cambardella et al. (1994) to evaluate the spatial interrelation between two related soil properties, the cross-semivariograms exhibited a strong negative spatial interdependence between soil PR and θ_m, ε_T, and lnK_s. Table 3 gives the structural correlation coefficients from the three models of co-regionalization for PR with θ_m, ε_T and lnK_s whose cross-semivariograms are also illustrated in figures 3A, 3B, and 3C, respectively. The cross-semivariograms were negative in all cases indicating that values of the two variables tend to vary independently.

The structural variance values from the models were smaller than 0.25, suggesting that spatial interrelationships are strong between soil properties considered in this study. The nugget effect values for all three interrelated models were very small and close to zero (table 3, figs. 3A, 3B, and 3C), indicating a spatial smoothing among adjacent sampling points (Journel and Huijbregts, 1978; Davis, 1986; Vieira and Gonzalez, 2003). These results showed that significant spatial relationships existed among soil properties at the

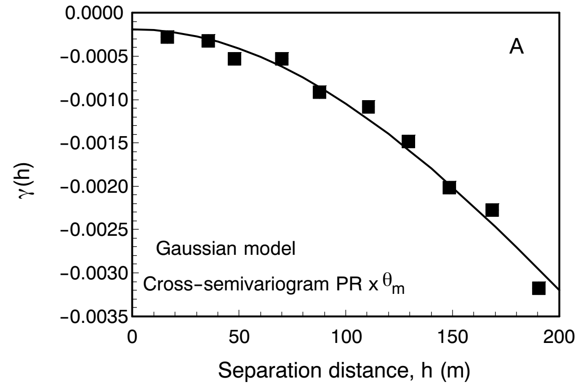

Figure 3A. Cross-semivariogram of PR × θ_m.

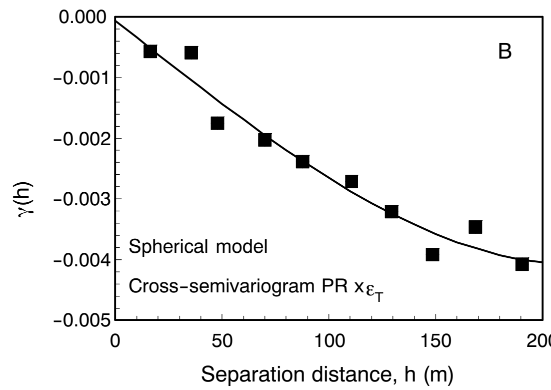

Figure 3B. Cross-semivariogram of PR × ε_T.

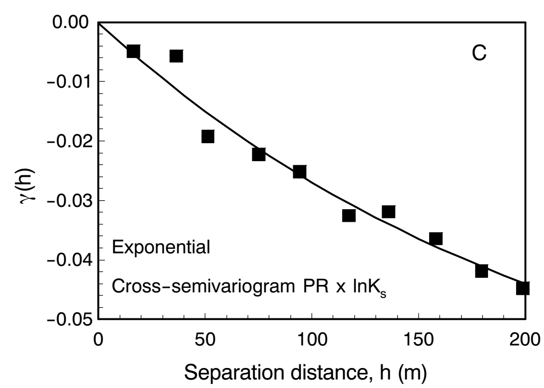

Figure 3C. Cross-semivariogram of PR × lnK_s.

Table 3. Coefficients of the theoretical cross-semivariogram models for combination of soil properties.

Soil Properties[a] Combination	Model	Nugget, C_0	Sill, $C_0 + C$	Nugget Ratio, $\frac{C_0}{C_0 + C}$	Range A (m)	RSS[b]	R^2
PR × θ_m	Gaussian	-0.0019	-0.0102	0.19	334	1.4×10^{-7}	0.98
PR × ε_T	Spherical	-0.00006	-0.0041	0.02	216	6.4×10^{-7}	0.96
PR × lnK_s	Exponential	-0.0001	-0.0736	0.001	220	5.9×10^{-5}	0.97

[a] PR is soil penetration resistance, θ_m is soil moisture content, ε_T is soil total porosity, and K_s is saturated hydraulic conductivity.
[b] RSS is the residual sums of squares for the theoretical cross-semivariogram models.

same location. The higher soil PR values are associated with lower θ_m, ε_T, and K_s for a sandy loam soil in a CRP grassland production field.

The cross-semivariograms results of PR with θ_m, ε_T, and $\ln K_s$ data sets were used in co-kriging analysis and calculations (co-kriged maps not shown). The results showed that both kriged and co-kriged predictions were close to zero and about the same after they were evaluated and compared using cross-validation statistical methods (see table 4). Both the mean difference error (MDE) and the mean square error (MSE) showed that co-kriging did not improve predictions for PR with θ_m, ε_T, and $\ln K_s$ data compared to kriging (table 4). Thus, kriging is considered to be an accurate and adequate for spatial interpolation of soil properties used in this study.

Block Kriged Maps

Spatial prediction maps produced by the block kriging procedure using the semivariogram coefficients in table 2 for selected soil properties are shown in figures 4A-4F. The spatial distribution of θ_m follows the topographical feature of the field where the land steadily slopes from north-west to south-east at approximately 2% (fig. 1). The values of θ_m were small (0.084 to 0.091 g g^{-1}) in the north-western corner and gradually increased (0.111 to 0.118 g g^{-1}) toward south-eastern corner of the field (fig. 4A). Consequently, comparison of areas relatively high in θ_m to areas high in clay content (20 to 23%) generally showed direct spatial relationships with the highest values of θ_m and clay content occurred at the lowest field topographical positions (Jabro et al., 2006).

The spatial map of soil ε_T indicated that larger ε_T were located in the south and south-eastern parts of the field extending from south and south-eastern to north and north-western areas of the field (fig. 4B). The spatial patterns of variation in soil ε_T were associated directly to spatial variations in clay contents within the field (Jabro et al., 2006). Moreover, the patterns of spatial variations in K_s were also directly correlated ($r = 0.99$, $P < 0.01$) to spatial variations in ε_T since K_s was empirically estimated from the ε_T related soil properties data.

The spatial PR predictions map (fig. 4C) shows a similar scenario with high PR values (2 to 2.5 MPa) on the western half and northern part of the field and low PR values (1 to 1.6 MPa) located on the eastern half of the field. There were obvious and semi-consistent spatial relationships between patterns of variation in soil PR and ε_T within the field. In general, areas where the PR values were low corresponded with high clay contents and ε_T in the soil.

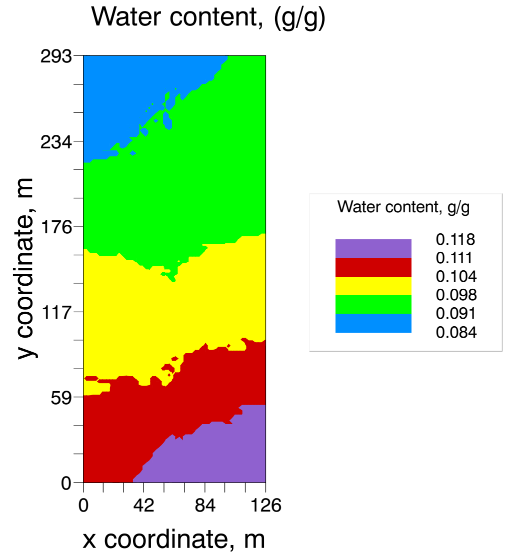

Figure 4A. Moisture content, θ_m.

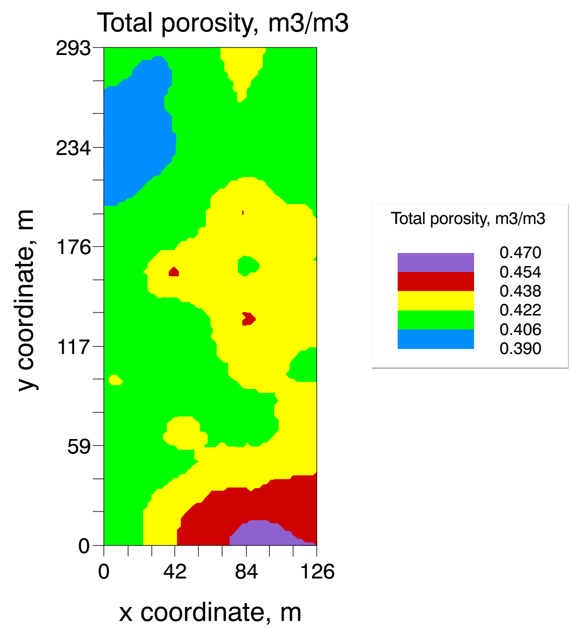

Figure 4B. Total porosity, ε_T.

Similarly, spatial distribution of ECe was also associated with the spatial distribution and variation of clay content in the soil. The largest ECe values were along the southern and eastern parts of the field, with smaller values along the

Table 4. Cross-validation statistics of kriging and co-kriging of soil properties.

	Kriging		Co-kriging	
Soil Property	MDE[a]	MSE[a]	MDE[a]	MSE[a]
Moisture content, θ_m (g g^{-1})	0.00014	0.000076	0.00018	0.000076
Total porosity, ε_T (m^3 m^{-3})	0.00042	0.00051	0.00014	0.00064
Penetration resistance, PR (MPa)	0.0015	0.053	0.0022	0.06
Hydraulic conductivity (K_s) (cm d^{-1})	0.0023	0.043	0.0024	0.058

[a] MDE is mean difference error, $MDE = \frac{1}{n}\sum_{i=1}^{n}\left|(A_i - P_i)\right|$ and MSE is a mean square error, $MSE = \frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2$, where A_i and P_i are actual and predicted values, respectively, at a location i, and n is the number of observations.

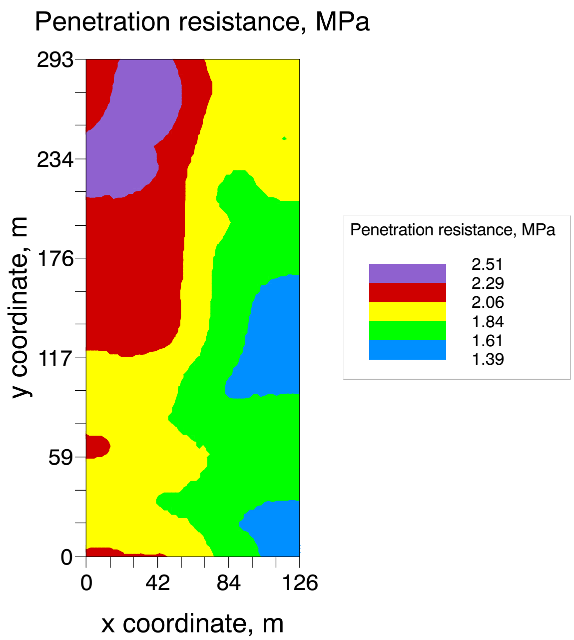

Figure 4C. Penetration resistance, PR.

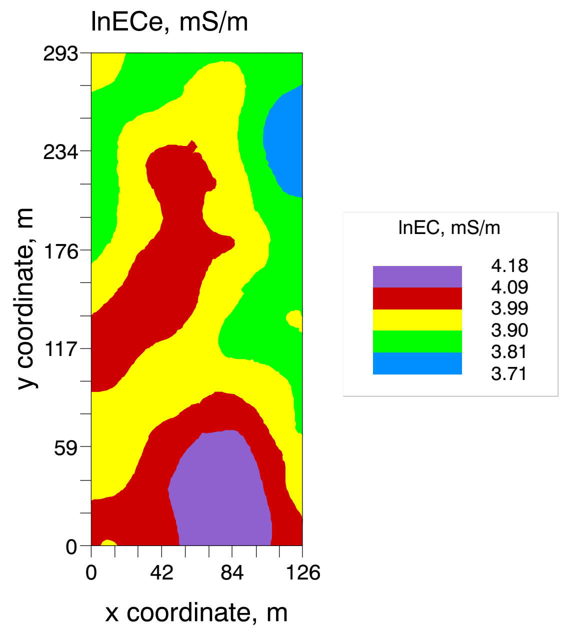

Figure 4E. Electrical conductivity, lnECe.

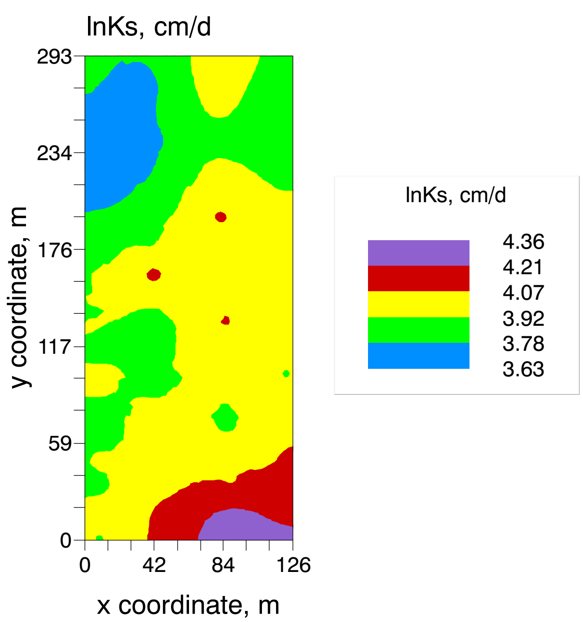

Figure 4D. Hydraulic conductivity, lnK_s.

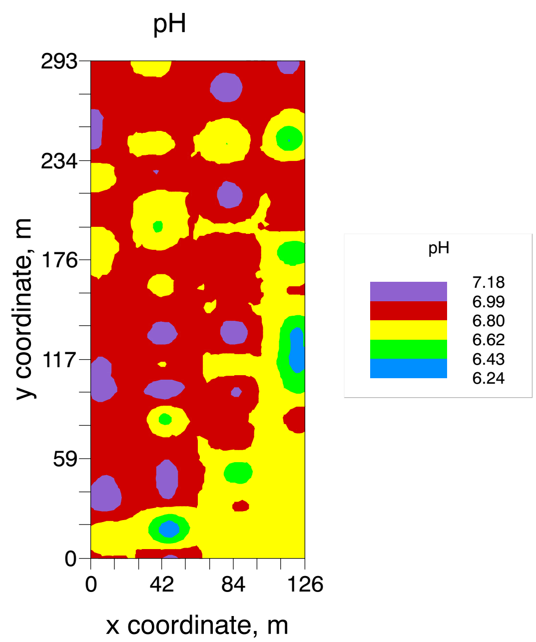

Figure 4F. Soil pH.

northern and northeastern field boundaries. In general, areas where soil ECe values were large (ECe = 4.09 to 4.18 mS m^{-1}) corresponded directly with higher contents of clay in the soil (20 to 23%) within the field because clay is generally higher in conductivity and tends to hold more water than sand and silt particles (Jabro et al., 2006).

Figure 4F shows spatial distribution patterns of pH within the CRP field. Two stretches of relatively high soil pH ran across the field with randomly distributed small high and low pH spots within the field. The spatial distribution of soil pH clearly followed topographical characteristics of the field where lower soil pH (6.62 to 6.80) dominated the south and southeastern areas in the lowest topographical position of the field while higher pH (6.80 to 6.99) dominated the northern and northwestern areas in the higher topographical positions. These results agreed with those found by Gaston et al. (2001) where soil pH was associated with clay and organic carbon contents in the lower topographical areas of the field.

Spatial statistics indicated that θ_m, ε_T, PR, K_s, ECe, pH, and clay content were spatially associated explaining some trends in soil variability within the field. The variations in the Ap horizon of CRP grassland may also be affected by other factors such as vegetation, previous farming practices, and weather conditions. For example, information about previous management indicates that soil erosion by wind and water occurred extensively prior to implementation of conservation practice and likely caused finer soil particles to be transported from higher to lower landscape positions causing differences in soil particle size distribution, pH, ECe, and water holding capacity. This soil particle transport, along with inherent topographical variations and characteristics, would be expected to influence the amount and type of biomass produced by both native and cultivated forage species, leading to spatial variability in soil organic matter content that then influences water holding capacity, organic carbon, pH, aggregation, pore space associated with water at field capacity level, and soil structure in the surface layer (Jabro et al., 2006). Spatial variability in these soil properties has been shown to influence the spatial distribution of crop yield and is thus considered an important factor when implementing site-specific irrigation and fertilizer practices (Russo, 1986b; Sadler et al., 2005). Russo (1986a) used a simplified crop response model to illustrate that spatial variability of soil moisture content and soil salinity lead to spatial variability in crop yield, especially under deficit soil moisture conditions. In a subsequent article (Russo, 1986b), the authors concluded that it is important to analyze the inherent spatial distribution of soil in a field when implementing improved irrigation management schemes and their simulated data suggests that 29% less irrigation water was required when applied based on soil properties than when applied uniformly. Similarly, Hedley and Yule (2009) concluded that 21.8 to 26.3% less water was needed where variable rate irrigation was implemented based on patterns in apparent soil electrical conductivity (ECa). Physical properties of soil may also affect N management, primarily because of their influence on soil water movement. Delgado (1999; 2001) observed different post-harvest soil NO_3-N concentrations in areas of a field that differed in soil texture. Subsequently, Delgado and Bausch (2005) reported a 50% reduction in nitrogen fertilizer inputs and an 85% reduction in NO_3-N leaching when soil spatial variability was managed using site-specific management. Finally, successful implementation of site-specific management practices depends on accurately describing variability of the pertinent soil properties. Characteristics of spatial relationships can have a significant impact on the success of various soil sampling strategies. For example, Corwin et al. (2003) concluded that knowledge of soil variability patterns can guide a directed soil sampling approach that may more efficiently provide information necessary to generate site-specific management recommendations. Our results provide further information about the spatial dependency of some of the primary soil parameters that influence site-specific management decisions.

Summary and Conclusions

The spatial variation of θ_m, ε_T, PR, lnK_s, lnECe, and pH at the 0- to 25-cm depth of the Ap horizon of a sandy loam soil within a field of CRP grassland was explored and assessed using classical and geostatistical methods. Results from both statistical approaches indicated that small to moderate spatial variability existed across the field for soil properties considered in this study. Cross-semivariograms exhibited a strong negative spatial interdependence between soil PR and θ_m, ε_T, and lnK_s. Both MDE and MSE showed that co-kriging did not improve predictions for PR with θ_m, ε_T, and lnK_s than kriging. Thus, kriging is considered to be an accurate and adequate method for spatial interpolation and evaluation of soil properties considered in this study. Spatial statistics indicated that, θ_m, ε_T, PR, K_s, ECe, pH, and clay content were spatially associated explaining some trends in soil variability within the field. The variations in soil properties in the Ap horizon of CRP grassland may be affected by topographic position characteristics, erosion, vegetation history, weather conditions, and previous farming practices.

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